

# Improving Performance of Texture Based Face Recognition Systems by Segmenting Face Region

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**Abstract**— Textures play an important role in recognition of images. This paper investigates the efficiency of performance of three texture based feature extraction methods for face recognition. The methods for comparative study are Grey Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP) and Elliptical Local Binary Template (ELBT). Experiments were conducted on a facial expression database, Japanese Female Facial Expression (JAFFE). With all facial expressions LBP with 16 vicinity pixels is found to be a better face recognition method among the tested methods. Experimental results show that classification based on segmenting face region improves recognition accuracy.

**Keywords**— face recognition, face anthropometric measures, grey level co-occurrence matrix, local binary pattern, elliptical local binary template, chi-square statistic.

## I. INTRODUCTION

Face recognition plays an important role in the field of computer vision, and has many real-world applications including biometric authentication and computer-human interaction. Many traditional face recognition systems use intensity of images that are very sensitive to slight variations in lighting, pose and expression. One of the most important characteristics that can be used to recognize a person is a texture feature. Some of the features that are used to recognize faces are geometric, photometric, 3-D and skin texture. Texture plays a vital role in recognition of objects and scenes. Texture based facial recognition is an ongoing research. Textures are specified by the statistical distribution of spatial dependencies of gray level properties [18]. Grey level co-occurrence matrix based features are first introduced by Haralick in the year 1979. The grey level co-occurrence matrices of an image estimate second-order statistics [13]. Ojala et al. introduced LBP operator that helps one to extract texture pattern in an image. LBP operators are easy to compute. So they are suitable for real time applications. One of the advantages of LBP is economy of memory [10]. ELBT is a modification of LBP, which uses LBP operator for histogram computation. ELBT differs from LBP in such a way that vicinity pixels lie on an ellipse rather than circle [10].

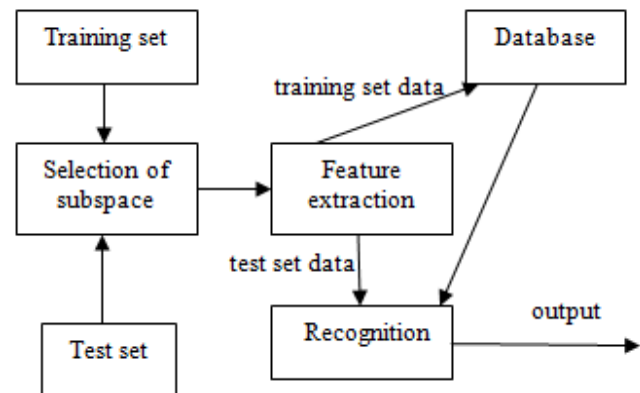
### A. Motivation and Justification

Nowadays face recognition has become a very challenging aspect because of the variations in pose, illumination and orientation of face images. It is still difficult to develop an automatic system for face recognition. Texture based feature extraction methods help us to extract uniformity, roughness, lightness, density, regularity, linearity, phase, directionality, randomness, coarseness, fineness, granulation, smoothness,

etc., of the texture as a whole [2]. GLCM, LBP and ELBT are few among existing texture feature extraction methods. Face recognition systems that use ELBT signs and their modification give high results on both speed and accuracy [10].

### B. Outline of the Approach

This paper analyzes the performance of three methods: GLCM, LBP and ELBT. In all the methods a subspace in the face is selected for recognition by face anthropometric measure (distance between eye centers). Eye centers are selected manually. JAFFE database [12] is used for the experiment. Following figure is an outline of the process.



The latter part of this study is organized as follows: Section (2) explains the methods. Section (3) describes the classification algorithm and distance measures used. Section (4) focuses on results and discussion. Section (5) deals with conclusion.

## II. TEXTURE FEATURE EXTRACTION METHODS

### A. GLCM

This method helps one to statistically sample the way certain grey-levels occur in relation to other grey-levels. The grey level co-occurrence matrix  $P_d$  for a displacement vector  $d = (dx, dy)$  is defined as follows. Every entry  $(i, j)$  of  $P_d$  is the frequency of occurrences of two pixels, with grey-levels  $i$  and  $j$  appearing in the window separated by a displacement vector  $d$ . As an example, consider the following  $4 \times 4$  image containing three different grey values:

1	1	0	0
1	0	0	0
0	0	2	2
0	0	2	2

The  $3 \times 3$  grey level co-occurrence matrix for this image for a displacement vector of  $d = (0, 1)$  is given as follows:

$$P_{(0,1)} = \begin{matrix} & 0 & 1 & 2 \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{pmatrix} 5 & 0 & 2 \\ 2 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix} \end{matrix}$$

Here the entry (0, 0) of  $P_d$  is 5 because there are five pixel pairs of (0, 0) that are offset by (0, 1) amount. Table I lists some of the texture features that can be computed from the matrix.

TABLE 1. TEXTURE FEATURES

Angular Second Moment (ASM)	$\sum_{i,j} P_d^2(i,j)$
Entropy (ET)	$\sum_{i,j} P_d(i,j) \log_2 P_d(i,j)$
Maximum Probability (MP)	$\max_{i,j} (P_d(i,j))$
Inverse Difference (ID)	$\sum_{i,j} \frac{P_d(i,j)}{1 +  i - j }$
Inverse Difference Moment (IDM)	$\sum_{i,j; i \neq j} \frac{P_d(i,j)}{1 +  i - j ^2}$
Mean (M)	$\sum_{i,j} i * P_d(i,j)$

### B. LBP

The LBP method was first introduced by Ojala et al [14]. LBP operator labels every pixels by thresholding the 3\*3 neighborhood of the pixels with the center value and considers the result as a binary number as illustrated in the fig. 1. Then the histogram of the labels is used as texture descriptor [3].

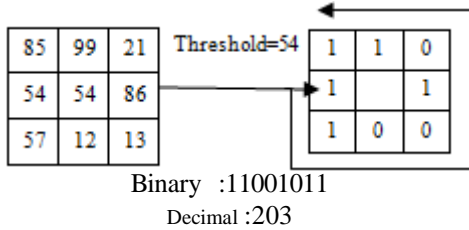


Fig. 1. Operation of LBP operator.

The LBP method can be regarded as a truly unifying approach. Instead of trying to explain texture formation on a pixel level, local patterns are formed. Each pixel is labeled with the code of the texture primitive that best matches the local neighborhood. Thus each LBP code can be regarded as a micro-texton. Local primitives detected by the LBP include spots, flat areas, edges, edge ends, curves and so on [20]. Uniform LBPs are used for economy of memory and to determine important local textures. LBP that has not more but two transitions from (0) to (1) or otherwise are called as uniform LBP. In LBP the vicinity pixels are on a circle with any radius. The number of dots on the circle may be chosen arbitrarily. For determining the values in the dots bilinear interpolation is used [10].

### C. ELBT

Methods for extracting texture features from face image, which

use LBT, have been recently attracting the researchers [10]. LBT was first introduced in 1996 for analyzing texture features in grey-scale images [14]. In ELBT vicinity pixels lie on ellipse relating to the central pixel. Let the vertical radius of the ellipse be  $vr$ , horizontal radius be  $hr$  and total number of vicinity pixel be  $m$ . Then the coordinates  $cix$  and  $ciy$  for each vicinity pixel will be computed using (2). Coordinates of vicinity dots are not always in the center of pixel; therefore bilinear interpolation is used to calculate them. The histogram for a region of the image shall be formed according to (4).

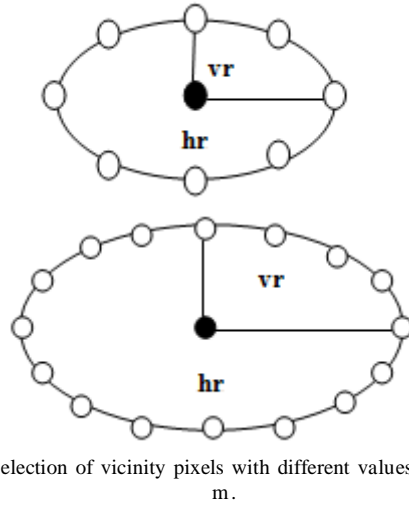


Fig. 2. Selection of vicinity pixels with different values of  $hr$ ,  $vr$  and  $m$ .

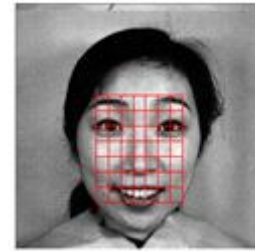


Fig. 3. 7x7 regions of face image.

$$R_i = \sqrt{\frac{hr^2 + vr^2}{hr^2 \sin^2 \theta_i + vr^2 \cos^2 \theta_i}} \quad (1)$$

$$cix = R_i \cdot \cos \theta_i, ciy = R_i \cdot \sin \theta_i, \quad (2)$$

$$\theta_i = \left[ \frac{360}{m} * (i - 1) \right]^\circ \quad (3)$$

$$Hi(kx, ky) = \sum_{x,y} I\{LBP(x,y) = L(i)\}, i = 1, \dots, P(P-1) + 3 \quad (4)$$

$$\text{where } L(i) = \begin{cases} 1, i - \text{true} \\ 0, i - \text{false} \end{cases}$$

### III. CLASSIFICATION PRINCIPLE

#### A. K-Nearest Neighborhood Classification

For classification k-nearest neighborhood algorithm is used. The algorithm is as follows.

- Every class of the training set is assigned to have unique tag value.
- Dissimilarity measure is found out for every image in the training set.
- Sort the images in the trained set by the chi square value obtained from the aforesaid step.
- The majority of the images that belong to same class is determined from the first three images which has the least chi square value.

#### B. Distance Measure

Dissimilarity between two objects can be measured using Chi square statistic ( $\chi^2$ ). Dissimilarity measure among observed (O) and expected (E) facial images are measured using following formula.

$$\chi^2(O, E) = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{(O_{ij} + E_{ij})} \quad (5)$$

In the above formula i,j indicates i<sup>th</sup> region j<sup>th</sup> feature value. Some region in the face has more importance than other, so weights can be assigned to every region in such a way that weight are assigned to regions depending on their importance in recognition of face. In such cases the following formula can be used.

$$\chi^2(O, E) = w_i \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{(O_{ij} + E_{ij})} \quad (6)$$

In formula (6)  $w_i$  is the weigh assigned to every region i.

### IV. EXPERIMENTS AND RESULTS

#### A. Experimental Setup

In this paper performance of three texture based methods GLCM, LBP and ELBT are evaluated. For testing JAFFE database is used. The database contains 213 images of 7 facial expressions posed by 10 Japanese female models. The methods are experimented in three ways: with single region, k×k region,

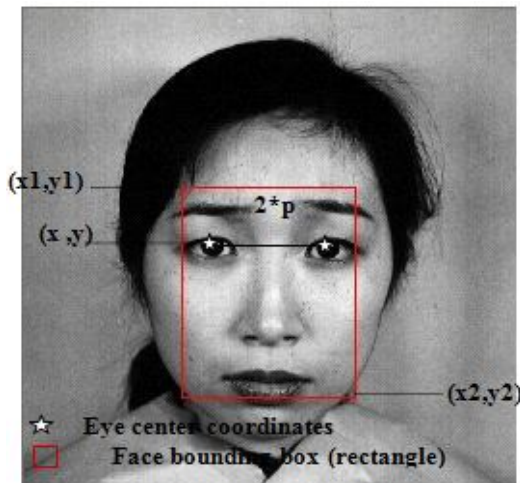


Fig. 4. Subspace selection by face anthropometric measure.

$$x1 = x - (p / 2) \quad (7)$$

$$y1 = y - p \quad (8)$$

$$x2 = (x + 3 * p) - (p / 2) \quad (9)$$

$$y2 = (y + 3 * p) - (p / 4) \quad (10)$$

and with weighted k×k region. To avoid complexity of using features of entire face, face anthropometric measure (distance between eye centers) is used to select a subspace in the face image [5] as shown in Fig. 4. by using (7)-(10). The eye centers are selected manually. In GLCM method grey level co-occurrence matrices are computed for displacement vectors (0, 1), (1, 0) and (1, 1). Then texture features listed in Table I are computer for individual matrix and are averaged to get final value [13]. For the methods LBP and ELBT, vicinity pixels are computed using (1), (2) and (3). Number of vicinity pixels considered for LBP and ELBT are 16 by substituting the values hr and vr as 3 for LBP, and hr as 2 and vr as 3 for ELBT.

#### B. Experiment I – Single Region

In this experiment, the region selected for recognition is considered as a single region and features are computed for the entire region. A result of the experiment is shown in Table II.

#### C. Experiment II – With k×k Regions

For this experiment the selected region is divided into k×k region as shown in Fig. 3. and features are computed for individual regions separately. To recognize an image in the test set, the feature of one region is compared with the feature of the respective region in the trained images. The three methods are tested against 5×5 region and 7×7 region. Result of the experiment is given in Table II.

#### D. Experiment III – With Weighted k×k Regions

In this experiment, selected region in the face is divided into 7×7 region. And they are assigned some weight as in [10]. Fig. 5. Shows the applied weights. Experimental result is given in Table II.

2	1	1	1	1	1	2
2	4	4	3	4	4	2
1	1	1	2	1	1	1
0	1	1	2	1	1	0
0	1	1	1	1	1	0
0	1	1	2	1	1	0
0	1	1	1	1	1	0

Fig. 5. Weights applied for 7×7 region.

#### E. Analysis of the result

Results of the experiments show that multiple regioning method yields more accuracy than single regioning. 7×7 segmentation method gives better result than 5×5 segmentation method. The recognition rate of GLCM, LBP and ELBT shows that experiment II and III is better than experiment I for recognizing facial expression images.

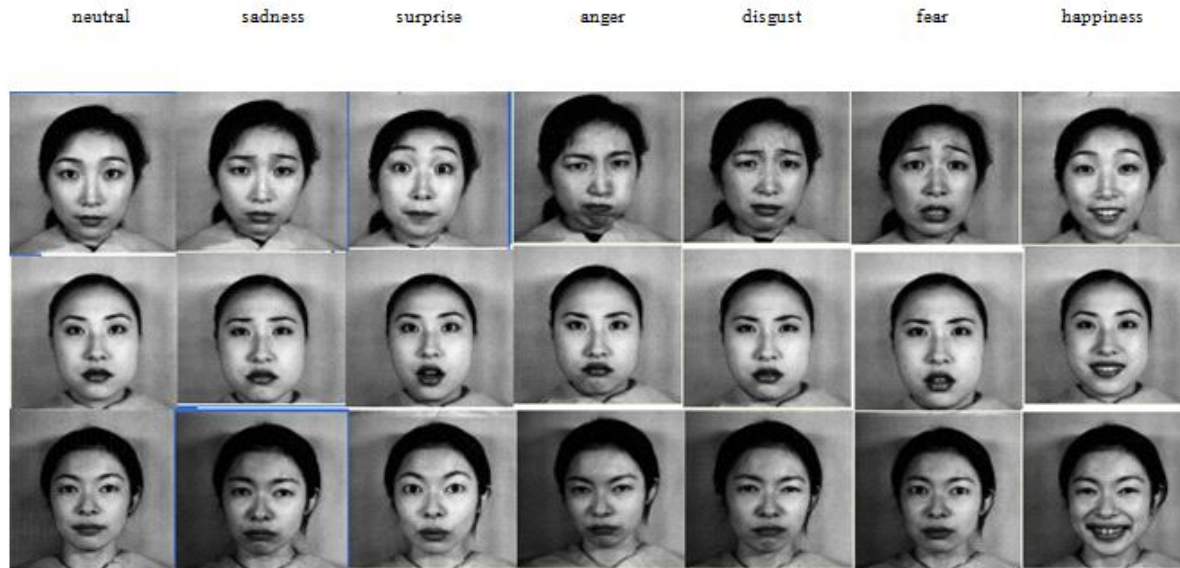


Fig. 6. Sample images from JAFFE

TABLE II. ACCURACY OF RECOGNITION

Method used for recognition	Training Set	Test Set	Experiment I - Single region	Experiment II		Experiment III - Weighted 7×7 regions
				5×5 regions	7×7 regions	
GLCM	131	76	72%	97.36%	98.68%	98.68%
ELBT			96%	97.36%	98.68%	98.68%
LBP			98.68%	98.68%	98.68%	100%

## V. CONCLUSION

GLCM, LBP and ELBT methods were evaluated by using JAFFE database. With all the expressions in the database, accuracy of recognition of LBP with 16 vicinity pixels is found to be better than the other two methods. When advanced version of LBP is experimented with, results better than the one obtained here can be achieved. Experiment I, II & III show that weighted regioning method works well for expression databases. Texture features can be combined with geometry based features to enhance the performance of face recognition techniques. It is observed from the experiments that face recognition techniques yield better results when face region under consideration is divided into many sub regions

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